pomponio_alessandro_2020_06_19

February 6, 2021

1 Alessandro Pomponio - 0000920265

1. load the data into a dataframe df, show its size and head, eliminate the rows containing null values and show the number of remaining rows (2pt)
2. produce a pairplot of the numeric columns of df and comment relevant situations (2pt)
3. Produce a box plot of the numeric columns of df and comment relevant situations (2pt)
4. Produce the correlation matrix of the data and eliminate the redundant attributes, if it is adequate (4pt) • For example, if attributes a and b have high correlation (e.g. absolute value higher than 0.95) one of the two can be eliminated • Refer to this page for the generation of the correlation matrix
5. Split the reduced data: store the first column in a vector keys and the others in a matrix X (2pt)
6. Find the best clustering scheme for the data (possibly reduced after step 4) with a method of your choice, plot global silhouette index for an appropriate range of hyperparameter(s) and show the chosen hyperparameter(s) (4pt)
7. fit the clustering scheme to y, then produce the silhouette plot using the function plot_silhouette contained in the attached file (4pt)
8. Perform a logarithmic transformation of the data (4pt) • This means simply to apply the log function of numpy • If one of the columns has zero or negative values, avoid its transformation
9. repeat point 5 and 6 above and comment the comparison with the result of point 6

[1]:
```
# Imports
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, silhouette_samples
from plot_silhouette import plot_silhouette

# Variables
file_name = 'country_stats.csv'
separator = ','
random_state = 42

# Directives
%matplotlib inline
np.random.seed(random_state)
```

1.1 1. load the data into a dataframe df, show its size and head, eliminate the rows containing null values and show the number of remaining rows (2pt)

[2]:
```python
# Load the data into a dataframe df
df = pd.read_csv(filepath_or_buffer = file_name, sep = separator)

# Show its size
print(f"The dataframe contains {df.shape[0]} rows and {df.shape[1]} columns")
```

```
The dataframe contains 242 rows and 8 columns
```

[3]:
```python
# Show its head
df.head()
```

[3]:
```
     Country Name  GDP at market prices (constant 2005 US$)  \
0     Afghanistan                              1.593680e+10
1         Albania                              1.192695e+10
2         Algeria                              1.612073e+11
3  American Samoa                              5.760000e+08
4         Andorra                              3.355695e+09

   GDP at market prices (current US$)  GDP per capita (constant 2005 US$)  \
0                        1.593680e+10                          553.300289
1                        1.192695e+10                         4094.358832
2                        1.612073e+11                         4463.394675
3                        5.760000e+08                        10352.822762
4                        3.355695e+09                        39736.354063

   GDP per capita (current US$)  Internet users (per 100 people)  \
0                    553.300289                              4.0
1                   4094.358832                             45.0
2                   4463.394675                             12.5
3                  10352.822762                              NaN
4                  39736.354063                             81.0

   Population growth (annual %)  Population, total
0                      2.812617         28803167.0
1                     -0.496462          2913021.0
2                      1.821358         36117637.0
3                     -1.054862            55637.0
4                     -0.015393            84449.0
```

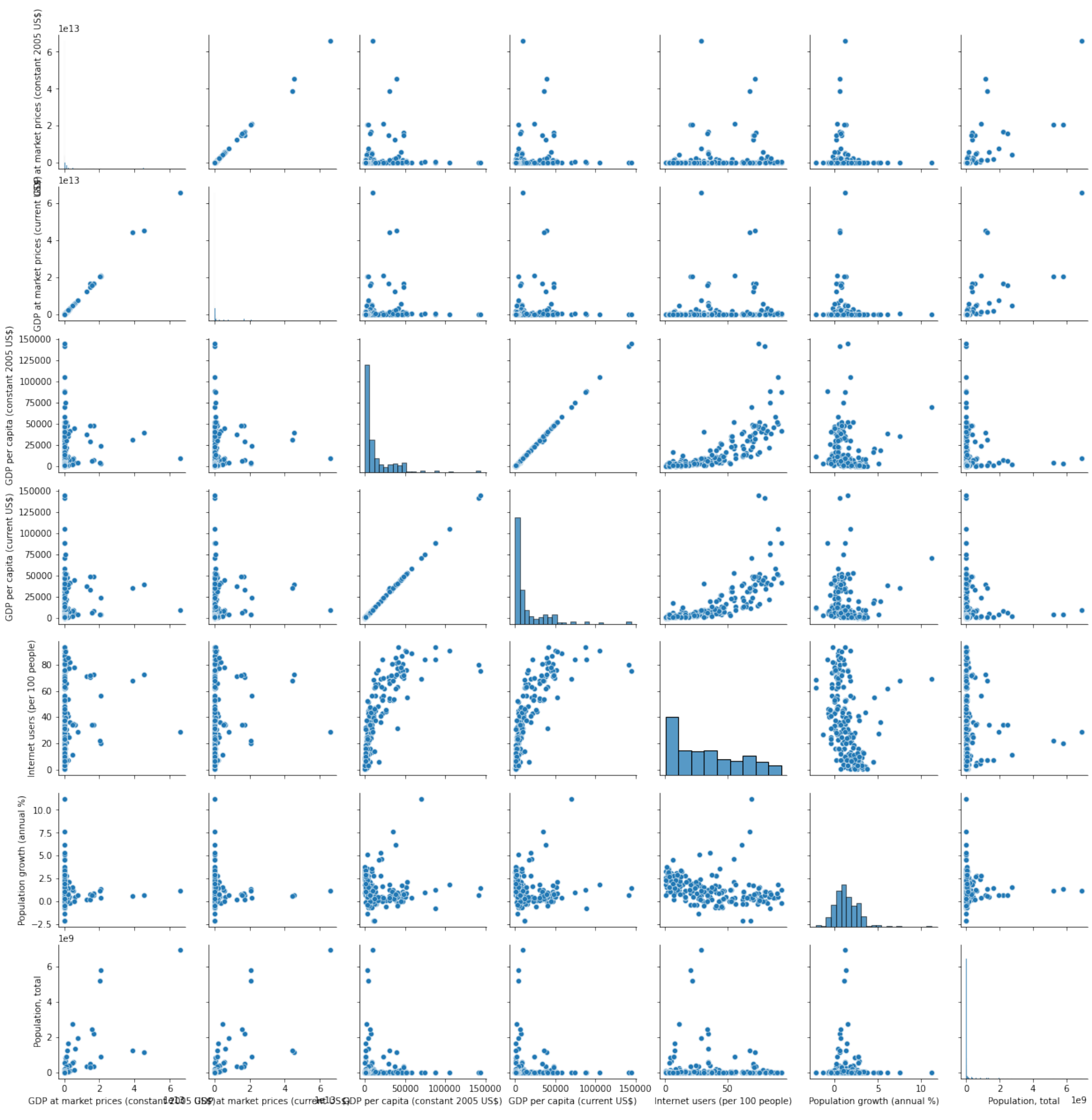
[4]:
```python
# Eliminate the rows containing null values and show the number of remaining␣
 ↪rows
df_cleaned = df.dropna()

# Show the number of remaining rows
print(f"The cleaned dataframe contains {df_cleaned.shape[0]} rows")
```

```
The cleaned dataframe contains 221 rows
```

1.2 2. produce a pairplot of the numeric columns of df and comment relevant situations (2pt)

[5]:
```python
# We only want the numeric columns, so we will temporarily drop the 'Country Name' column
X = df_cleaned.drop('Country Name', axis = 1)
sns.pairplot(X)
```

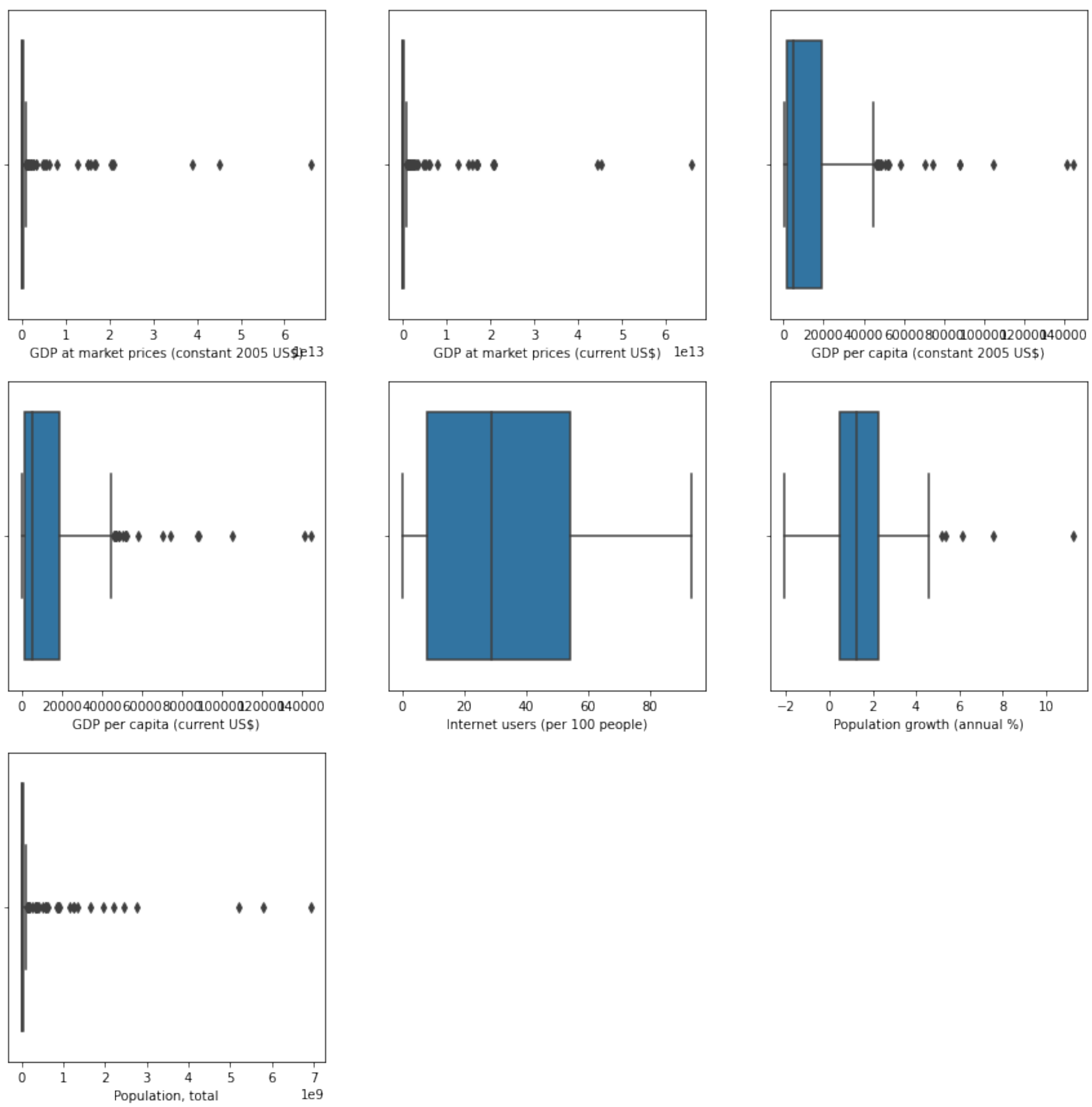
[5]:
```
<seaborn.axisgrid.PairGrid at 0x10934d6aa00>
```



The pairplots don't seem to highlight any particular situation, the points seem to be grouped together quite often, usually along one of the axes. Only certain plots like (2,4); (3,4); (4,2) (0-indexed) seem to show some more interesting configurations.

1.3 3. Produce a box plot of the numeric columns of df and comment relevant situations (2pt)

[6]:
```
# We will create a big figure and plot them one by one as subplots
plt.figure(figsize=(15,15))
pos = 1
for i in X.columns:
    plt.subplot(3, 3, pos)
    sns.boxplot(X[i])
    pos += 1
```



From these plots, we can see that in certain plots, like "GDP at market prices (constant 2005 US)", "$GDPatmarketprices(currentUS)$" and "Population, total" the values are compressed in one area and there are quite a few outliers; the same, although in a less extreme fashion can be said for the "GDP per capita (constant 2005 US)"and"$GDPpercapita(currentUS)$", although the median value tends to be on the low end of the spectrum. The "Population growth (annual %)" plot is much more balanced and with very few outliers, while the "Internet users (per 100 people)" plot does not have any outlier at all.

1.4 4. Produce the correlation matrix of the data and eliminate the redundant attributes, if it is adequate (4pt)

- *For example, if attributes a and b have high correlation (e.g. absolute value higher than 0.95) one of the two can be eliminated*

We will use Pandas's `corr()` function to obtain the correlation matrix

[7]:
```
correlation_matrix = X.corr()
correlation_matrix
```

[7]:
```
                                          GDP at market prices (constant 2005
US$)  \
GDP at market prices (constant 2005 US$)
1.000000
GDP at market prices (current US$)
0.998671
GDP per capita (constant 2005 US$)
0.082985
GDP per capita (current US$)
0.089343
Internet users (per 100 people)
0.140434
Population growth (annual %)
-0.103056
Population, total
0.743659

                                          GDP at market prices (current US$)  \
GDP at market prices (constant 2005 US$)                            0.998671
GDP at market prices (current US$)                                  1.000000
GDP per capita (constant 2005 US$)                                  0.084445
GDP per capita (current US$)                                        0.091601
Internet users (per 100 people)                                     0.143265
Population growth (annual %)                                       -0.103523
Population, total                                                   0.731674

                                          GDP per capita (constant 2005 US$)  \
GDP at market prices (constant 2005 US$)                            0.082985
GDP at market prices (current US$)                                  0.084445
```

```
GDP per capita (constant 2005 US$)                                     1.000000
GDP per capita (current US$)                                           0.999829
Internet users (per 100 people)                                        0.757132
Population growth (annual %)                                          -0.101623
Population, total                                                     -0.076738

                                        GDP per capita (current US$)  \
GDP at market prices (constant 2005 US$)                    0.089343
GDP at market prices (current US$)                          0.091601
GDP per capita (constant 2005 US$)                          0.999829
GDP per capita (current US$)                                1.000000
Internet users (per 100 people)                             0.758325
Population growth (annual %)                               -0.102485
Population, total                                          -0.075101

                                        Internet users (per 100 people)  \
GDP at market prices (constant 2005 US$)                       0.140434
GDP at market prices (current US$)                             0.143265
GDP per capita (constant 2005 US$)                             0.757132
GDP per capita (current US$)                                   0.758325
Internet users (per 100 people)                                1.000000
Population growth (annual %)                                  -0.356460
Population, total                                             -0.062403

                                        Population growth (annual %)  \
GDP at market prices (constant 2005 US$)                   -0.103056
GDP at market prices (current US$)                         -0.103523
GDP per capita (constant 2005 US$)                         -0.101623
GDP per capita (current US$)                               -0.102485
Internet users (per 100 people)                            -0.356460
Population growth (annual %)                                1.000000
Population, total                                          -0.037483

                                        Population, total
GDP at market prices (constant 2005 US$)          0.743659
GDP at market prices (current US$)                0.731674
GDP per capita (constant 2005 US$)               -0.076738
GDP per capita (current US$)                     -0.075101
Internet users (per 100 people)                  -0.062403
Population growth (annual %)                     -0.037483
Population, total                                 1.000000
```

Unsurprisingly, the correlation matrix shows how the GDP features expressed in both 2005 US$ and current US$ are very highly correlated, we will drop the columns with current US$ representations, as the data points seem to be more clumped up in them

[8]:
```python
columns_to_drop = ['GDP at market prices (current US$)', 'GDP per capita␣
↪(current US$)']
X = X.drop(columns_to_drop, axis = 1)

# Check that everything went as we'd expect
X.head()
```

[8]:
```
   GDP at market prices (constant 2005 US$)  \
0                              1.593680e+10
1                              1.192695e+10
2                              1.612073e+11
4                              3.355695e+09
5                              8.247091e+10

   GDP per capita (constant 2005 US$)  Internet users (per 100 people)  \
0                          553.300289                              4.0
1                         4094.358832                             45.0
2                         4463.394675                             12.5
4                        39736.354063                             81.0
5                         3529.053482                              2.8

   Population growth (annual %)  Population, total
0                      2.812617         28803167.0
1                     -0.496462          2913021.0
2                      1.821358         36117637.0
4                     -0.015393            84449.0
5                      3.570099         23369131.0
```

1.5 5. Split the reduced data: store the first column in a vector keys and the others in a matrix X (2pt)

We had already stored the reduced data in X, so we will just save the first column of the dataframe in y

[9]:
```python
y = df['Country Name']
```

1.6 6. Find the best clustering scheme for the data (possibly reduced after step 4) with a method of your choice, plot global silhouette index for an appropriate range of hyperparameter(s) and show the chosen hyperparameter(s) (4pt)

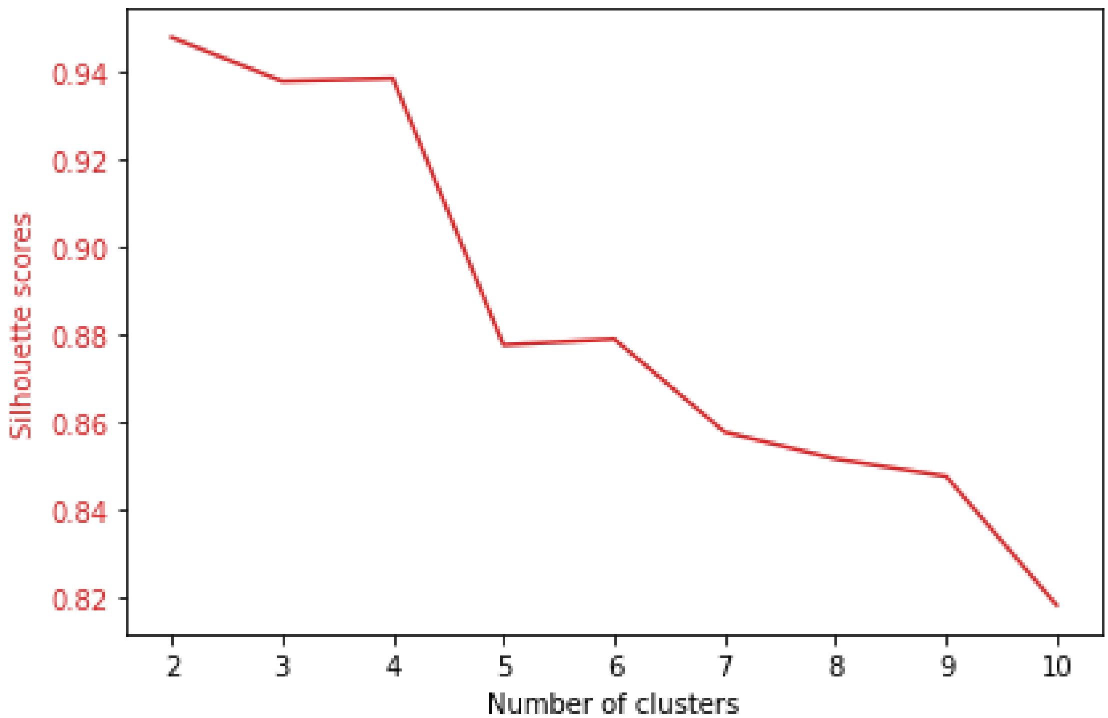
In order to find a clustering scheme, we will use K-means with the elbow method, ranging from 2 to 10 clusters

[10]:
```python
# Range of possible clusters
k_range = range(2,11)

# Silhouette Score as measure
```

```
silhouette_scores = []

for i in k_range:

    km = KMeans(n_clusters = i,
                init = 'k-means++',
                n_init = 10,
                max_iter = 300,
                random_state = random_state)

    y_km = km.fit_predict(X)
    silhouette_scores.append(silhouette_score(X,y_km))
```

Plot silhouette scores

[11]:
```
fig, ax = plt.subplots()
color = 'tab:red'
ax.set_xlabel('Number of clusters')
ax.set_ylabel('Silhouette scores', color=color)
ax.plot(k_range, silhouette_scores, color=color)
ax.tick_params(axis='y', labelcolor=color)
fig.tight_layout()
plt.show()
```



The silhouette scores plot tells us that we achieve the best results with 2 clusters

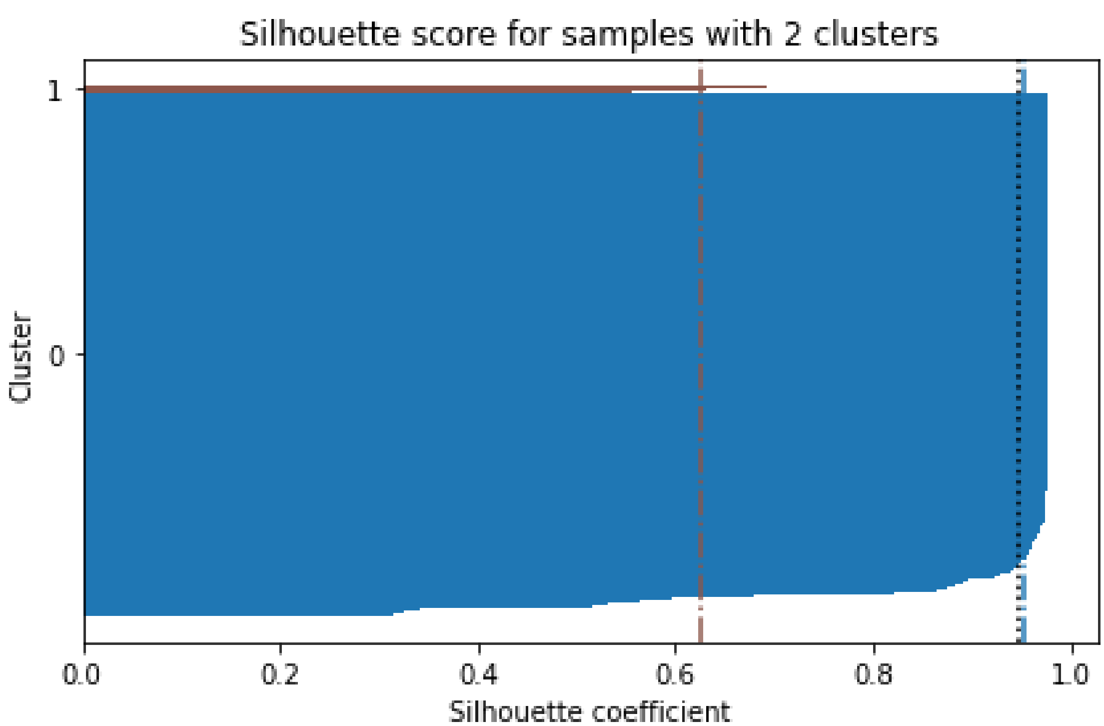
[12]:
```
# 2 is our starting point for the range
best_k = np.argmax(silhouette_scores) + 2
```

1.7 7. fit the clustering scheme to y, then produce the silhouette plot using the function plot_silhouette contained in the attached file (4pt)

[13]:
```
km = KMeans(n_clusters = best_k,
            init = 'k-means++',
            n_init = 10,
            max_iter = 300,
            random_state = random_state)

# We need the appropriate value of y_km with our best_k
y_km = km.fit_predict(X)

# Fit the clustering scheme to y
km.fit(X, y = y)
```

[13]:
```
KMeans(n_clusters=2, random_state=42)
```

[14]:
```
# produce the silhouette plot using the function plot_silhouette
silhouette_score_samples = silhouette_samples(X, y_km, metric='euclidean')
plt.title(f'Silhouette score for samples with {best_k} clusters')
plot_silhouette(silhouette_score_samples, y_km)
```



1.8 8. Perform a logarithmic transformation of the data (4pt)

- *This means simply to apply the log function of numpy*
- *If one of the columns has zero or negative values, avoid its transformation*

[15]:
```
for column in X.columns:

    # We don't want to transform columns with values
    # Lower than or equal to zero
    if len(X[column]) != sum(np.greater(X[column], 0)):
        continue

    X[column] = np.log(X[column])
```

[16]:
```
# Check the results
X
```

[16]:
```
     GDP at market prices (constant 2005 US$)  \
0                                   23.491897
1                                   23.202067
2                                   25.805957
4                                   21.933925
5                                   25.135711
..                                        …
237                                 22.910788
238                                 31.819987
239                                 24.154240
240                                 23.732189
241                                 23.039937

     GDP per capita (constant 2005 US$)  Internet users (per 100 people)  \
0                              6.315901                         1.386294
1                              8.317365                         3.806662
2                              8.403665                         2.525729
4                             10.590022                         4.394449
5                              8.168785                         1.029619
..                                  …                                …
237                            7.757359                         3.621671
238                            9.160766                         3.362250
239                            7.177196                         2.513656
240                            7.288390                         2.302585
241                            6.579223                         1.856298

     Population growth (annual %)  Population, total
```

```
0                         2.812617          17.175996
1                        -0.496462          14.884701
2                         1.821358          17.402292
4                        -0.015393          11.343903
5                         3.570099          16.966927
..                             …                 …
237                       2.898629          15.153429
238                       1.218629          22.659220
239                       2.713034          16.977044
240                       2.883152          16.443798
241                       1.976756          16.460714

[221 rows x 5 columns]
```

1.9 9. repeat point 5 and 6 above and comment the comparison with the result of point 6 (2pt)

1.9.1 Point 5

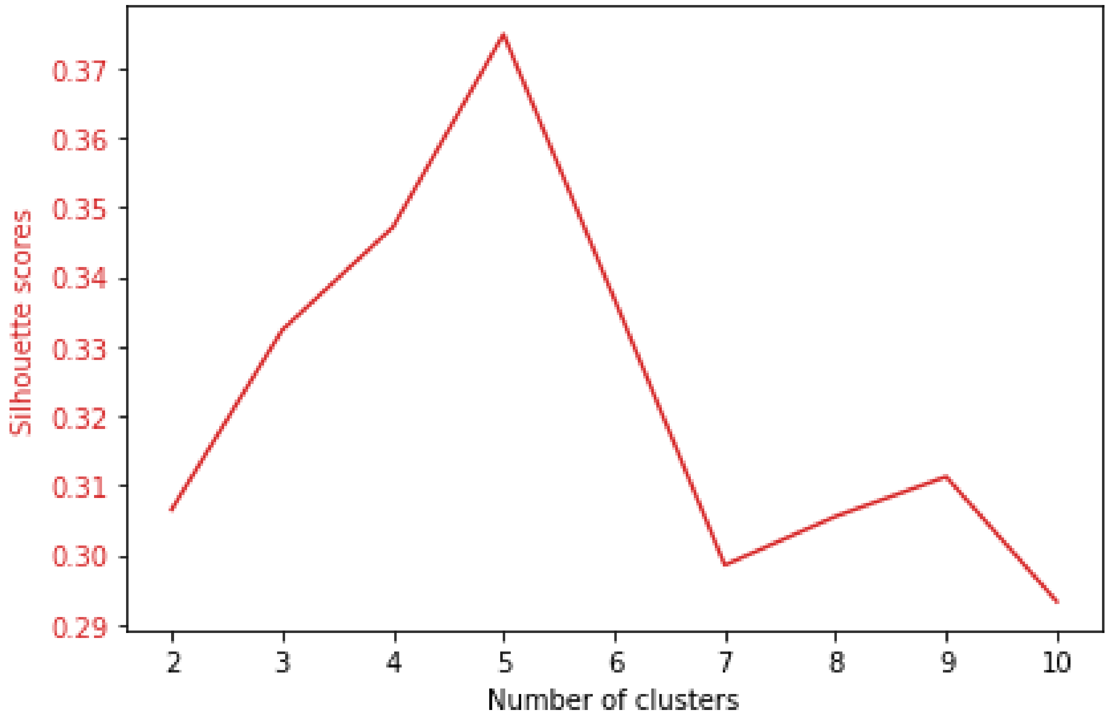
[17]:
```python
new_X = X.drop('GDP at market prices (constant 2005 US$)', axis = 1)
new_y = X['GDP at market prices (constant 2005 US$)']
```

1.9.2 Point 6

[18]:
```python
# Range of possible clusters
k_range = range(2,11)

# Silhouette Score as measure
silhouette_scores = []

for i in k_range:

    km = KMeans(n_clusters = i,
                init = 'k-means++',
                n_init = 10,
                max_iter = 300,
                random_state = random_state)

    new_y_km = km.fit_predict(new_X)
    silhouette_scores.append(silhouette_score(new_X,new_y_km))
```

[19]:
```python
fig, ax = plt.subplots()
color = 'tab:red'
ax.set_xlabel('Number of clusters')
ax.set_ylabel('Silhouette scores', color=color)
ax.plot(k_range, silhouette_scores, color=color)
ax.tick_params(axis='y', labelcolor=color)
fig.tight_layout()
```

```
plt.show()
```



By dropping the column 'GDP at market prices (constant 2005 US$)', the silhouette score now tells us that the best clustering scheme would involve 5 clusters, instead of 2